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THE ROLE OF CHATGPT AND HIGHER-ORDER THINKING SKILLS AS PREDICTORS OF PHYSICS INQUIRY

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Abstract. *The role of ChatGPT and higher-order thinking skills (HOTS) as predictors of physics inquiry among upper-secondary students has yet to be widely explored. Therefore, this research aimed to examine upper-secondary students' role in ChatGPT (convenience and quality (CQ), motivation and engagement (ME), and accuracy and trust (AT)) and HOTS as predictors of physics inquiry. Data were collected from 334 upper-secondary students in Indonesia through online questionnaires and analyzed with SPSS software using correlation and multiple linear regression. The results showed that CQ had the strongest correlation with HOTS, with significant predictors being response speed, concept linkage, and explanation quality. The ME dimension was also significantly correlated with HOTS, with increased motivation to learn and enjoyment in learning as key predictors. Lastly, the AT dimension significantly correlated with HOTS, where the accuracy of information and students' trust in it were essential predictors. These findings indicate that ChatGPT has the potential to enhance inquiry-based learning in physics by effectively supporting the development of HOTS.*

Keywords: *physics inquiry, ChatGPT, higher-order thinking skills, correlation, multiple linear regression, AI in education*

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Introduction

Fostering a deeper understanding of scientific principles requires an approach that actively engages students in the learning process. Physics inquiry is a specialized form of inquiry-based learning (IBL) that prompts active students' engagement in exploring, experimenting, and reflecting critically on physical phenomena (Prayogi & Yuanita, 2018). This learning process motivates scientific thoughts, leading to engagement in complex activities such as observing phenomena, asking relevant questions, formulating hypotheses, designing and conducting experiments, collecting data, and analyzing results (Novitra et al., 2021; Pedaste et al., 2015). Furthermore, the use of IBL enables students to understand fundamental physics concepts and also develop HOTS (Fadillah & Sahyar, 2023), including critical thinking, in-depth analysis, problem-solving, and decision-making (Antonio & Prudente, 2023; Maknun, 2020).

IBL is a commonly adopted method in physics education used to enhance students' 4C skills (critical thinking, creativity, collaboration, and communication) (Novitra et al., 2021). This method prompts active learning focusing on questioning, data analysis, and critical thinking to acquire meaningful knowledge in conducive environments (Kousloglou et al., 2023). However, the adoption of IBL presents significant challenges, namely lack of information resources, limited access to experimental tools, inadequate learning materials, and safety concerns (Asrizal et al., 2022; du Plessis & Mestry, 2019; Johnson & Tawfik, 2022; Stefanidou et al., 2022).

Based on the potentials, the complexity of physics inquiry can be overwhelming for some students, particularly those who may need more background knowledge or struggle with self-regulated learning (Higgins et al., 2021; Peel, 2020). The open-ended nature of inquiry tasks, including asking of questions and designing experiments, can lead to frustration when clear guidance is lacking (Käser & Schwartz, 2020; Pedaste et al., 2015). The varying levels of teacher guidance in IBL methods—ranging from unguided discovery to structured scaffolding significantly influences students' success (Lippmann, 2021). Some students may engage in surface-level learning or

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become disengaged without adequate support, thereby destabilizing the development of deep, reflective thinking (Festiyed et al., 2022; Novitra et al., 2021).

The complexity of physics inquiry was addressed by integrating technology into IBL leading to the realization of more accessible, and engaging learning experiences. Based on prior research, technology also enhances students' digital skills, which are increasingly essential in modern education (Becker et al., 2020; Pedaste et al., 2020). Artificial intelligence (AI), specifically the use of related tools such as ChatGPT is a technological advancement that offers significant potential in this context (Bettayeb et al., 2024; Festiyed et al., 2024).

ChatGPT, an AI-driven model that uses natural language processing (NLP), can interact with users in a conversational format (Shahzad et al., 2024). It assists students by answering questions, explaining complex concepts, including providing immediate, and properly designed feedback (Khan et al., 2024). The potential in physics inquiry is particularly essential for those struggling with certain aspects of the process, as well as experimental design or data analysis (Murtiningsih et al., 2024). For example, at the early stages of inquiry, namely formulating questions and hypotheses, ChatGPT tends to offer relevant suggestions based on the immeasurable knowledge base (Rospigliosi, 2023). During experimentation, it helps refine related methods or troubleshoot issues with respective investigational setups (Araújo & Saúde, 2024; Wang et al., 2024). Regarding data analysis, ChatGPT guides students in the selection and logical interpretation of appropriate analytical methods and results, respectively (Niloy et al., 2024).

Considering that this AI-driven model offers several advantages, its use in education is of concern. A major challenge is the risk of students becoming overly reliant on AI for problem-solving, which could destabilize the development of independent thinking and reflective skills (Krupp et al., 2024). The essence of physics inquiry focuses on motivating students to become autonomous learners who can analyze, evaluate, and solve problems creatively. However, over-dependence on AI may distract from this objective, leading to a more passive engagement with the material (Kim et al., 2021).

The research on how students perceive and interact with ChatGPT, specifically in the context of physics inquiry, needs to be completed, despite the promising potential of this technology. While some research had proven that ChatGPT enhanced student understanding of complex physics concepts by providing personalized feedback (Kotsis, 2024), a gap was detected in comprehending how specific features could be optimized to foster critical thinking and problem-solving skills. Factors such as the quality of interaction, accuracy of information provided, including impact on students' ME required further exploration (Lee et al., 2024; Tan, 2021). As physics inquiry often includes challenging problems (Festiyed et al., 2022; Novitra et al., 2021; Pedaste et al., 2015, 2020), the easy use and reliability of AI tools, namely ChatGPT, play a crucial role in influencing students' learning experiences (Albayati, 2024; Johnson et al., 2023; Tiwari et al., 2024).

Research Aim and Questions

This research examined three main aspects of ChatGPT role in the context of physics inquiry, namely CQ, ME, as well as AT. In addition, it addressed the following research questions:

RQ1. What is the correlation and predictive association between CQ on ChatGPT and HOTS?

RQ2. What is the correlation and predictive association between ME on ChatGPT and HOTS?

RQ3. What is the correlation and predictive association between AT on ChatGPT and HOTS?

RQ4. What are the most important predictive associations between CQ, ME, and AT on ChatGPT and HOTS?

Research Methodology

Design

This current research adopted a quantitative method, using a structured questionnaire to assess students' perceptions of ChatGPT and the impact on HOTS in the context of inquiry-based physics learning. The questionnaire focused on four main variables CQ, ME, AT, and HOTS, with each designed to capture different dimensions of ChatGPT role in supporting physics inquiry. The questions were formulated based on these predefined variables, validated internally by experts to ensure clarity and comprehensibility.

The questionnaire used a 4-point Likert scale, ranging from strongly disagree (1) to strongly agree (4), avoiding the neutral option in order to motivate participants to express more definitive opinions. This method was intended

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to reduce response ambiguity, thereby enhancing the validity of the data collected (Taherdoost, 2022). Table 1 shows the association between these four variables and physics inquiry.

Table 1
ChatGPT Role Association with Physics Inquiry

Variables	Association with physics inquiry
CQ	Understanding students' perception of the ease and quality of interaction with ChatGPT is essential to discerning whether the tool supports the processing of complex information, including addressing physics inquiry challenges.
ME	Students' perception of motivation and engagement when using ChatGPT is relevant to assess whether the tool increases active participation in inquiry activities, requiring deep engagement.
AT	It is crucial to ascertain students' perceptions of the veracity and credibility of information generated by the tool, as inquiry requires the use of valid and reliable data.
HOTS	Students' perception of ChatGPT contribution to critical thinking, in-depth concept analysis, and problem-solving was crucial for assessing the potential to help tackle complex physics problems in inquiry activities.

Note: convenience and quality (CQ); motivation and engagement (ME); accuracy and trust (AT); higher order thinking skills (HOTS)

Data Collection

The questionnaire was internally validated through expert review to ensure that the questions accurately measured the predefined variables and were easily understood by respondents. The validated questionnaire was then uploaded to Google Forms for online distribution. The survey link was shared through popular social media platforms, such as WhatsApp, targeting upper-secondary students in Indonesia to ensure wide and unbiased participation. Additionally, teachers from relevant schools were enlisted to distribute the link through class groups and other communication channels, ensuring that the sample was representative of the target population. Measures were taken to minimize bias, such as standardizing instructions provided to teachers and ensuring that all participants had equal access to the survey.

Prior to completing the survey, participants were provided with relevant information, and a consent form ensuring the research objectives were understood, voluntary participation, with the responses remaining confidential (Sloan et al., 2020). This method helped maintain ethical standards while maximizing data reliability and representativeness.

Participants

This present research focused on students using ChatGPT platform to facilitate physics learning. A convenience sampling method was adopted, with participants selected based on accessibility and willingness to participate. Considering that ChatGPT is relatively new among upper-secondary students in Indonesia, finding those already using this tool in physics learning was challenging. Therefore, participants were selected through social media platforms.

All participants were enrolled in schools that used *Merdeka Curriculum*. This national education framework prompted flexible and student-centered learning methods, focusing on critical thinking skills, in-depth concept analysis, independence, and the development of individual potential-all competencies in line with IBL (Fadillah et al., 2024). Cahya and Katemba (2023) explored the relevance of IBL in the *Merdeka Curriculum* for the development of HOTS. As a result, exposure to the *Merdeka Curriculum* enabled optimal assessment of ChatGPT potential in supporting the inquiry process in physics learning.

In line with this perspective, 334 students, aged between 14 and 18, from two provinces in Indonesia participated in the research, as shown in Table 2. This sample size met the minimum requirement for regression analysis ($N \geq 25$) (Jenkins & Quintana-Ascencio, 2020), ensuring the accuracy of the results. Moreover, of the total participants, there were 140 males (41.92%) and 194 females (58.08%). All participants used ChatGPT to support physics learning, and were exposed to inquiry elements in the framework of formal education.

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Table 2
Sample Characteristics (N = 334)

Criteria	Distribution	Frequency	Percentage (%)
Gender	Male	140	41.92
	Female	194	58.08
ChaGPT Users	Yes	334	100
	No	-	-
Use ChatGPT for physics learning	Yes	334	100
	No	-	-

Validation

Confirmatory factor analysis (CFA) was conducted using SmartPLS 4 software to validate whether the items measured were suitable for usage. CFA was carried out to ensure the quality of the research was maintained. Table 3 shows the results of the factor analysis for each item, with the core ones used for further evaluation. All items had good factor loadings, with values greater than .70 (Dash & Paul, 2021; Hair et al., 2021). Cronbach alpha (CA) and composite reliability (CR) values for all variables exceeded .80, while the average variance extracted (AVE) was greater than .50, depicting excellent reliability and validity (Dash & Paul, 2021; Hair et al., 2021). The reliability and validity of the data were verified, ensuring the credibility of the measurement instruments used.

Table 3
Measurements

Code	Items	Core items*	Loading
CQ: CA = .873, CR = .913, AVE = .724			
CQ1	ChatGPT helped in the easy understanding of physics concepts.	Ease of understanding	.830
CQ2	It enabled the connection of different physics concepts that were previously distinct.	Concept linkage	.835
CQ3	The tool provided quick responses to physics questions.	Speed of response	.868
CQ4	ChatGPT offered easier explanations than other learning resources.	Quality of explanation	.870
ME: CA = .904, CR = .933, AVE = .778			
ME1	The use of this tool motivates the learning of physics.	Increased motivation after using ChatGPT	.864
ME2	Interaction with ChatGPT makes learning physics more fun.	Enjoyment in learning	.915
ME3	The tool motivated students to learn physics.	Increased motivation to learn	.869
ME4	The use of ChatGPT as a tool in physics learning enabled a satisfactory feeling.	Satisfaction with using ChatGPT	.879
AT: CA = .866, CR = .918, AVE = .789			
AT1	The physics information provided by ChatGPT was accurate and in line with textbooks or other reliable sources.	Accuracy of information	.886
AT2	The tool provided up-to-date physics information.	Up-to-date information	.886
AT3	The physics related information from ChatGPT is as accurate as the one provided by my teacher.	Trust in information accuracy	.894
HOTS: CA = .861, CR = .915, AVE = .783			
HOTS1	ChatGPT motivated one to think critically about physics concepts.	Critical thinking	.880
HOTS2	The tool aided in the in-depth analysis of physics concepts.	In-depth concept analysis	.873
HOTS3	Interaction with ChatGPT improved the ability to solve complex physics problems.	Complex problem solving	.901

Note: *summary of items for easier interpretation; convenience and quality (CQ); motivation and engagement (ME); accuracy and trust (AT); higher order thinking skills (HOTS); Cronbach alpha (CA); composite reliability (CR); average variance extracted (AVE)

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Non-Response Bias and Assumption Checking

A test for non-response bias was conducted, as cross-sectional analyses are susceptible to this presumption, in order to ensure the accuracy of the research (Behl, 2022). This potential bias was addressed by comparing the initial and final responses of participants (Baabdullah, 2024). Furthermore, a two-sample *t*-test was adopted to compare the initial and final 20 responses of participants. The results obtained showed the *p*-value ranged from .186 to 1.000, depicting that the observed difference was insignificant ($p > .05$). This implied that non-response bias was insignificant in the evaluation process.

Preliminary assessments were conducted to determine the validity of the proposed assumptions, including normality, multicollinearity, and homoscedasticity tests, regarded as essential prerequisites for performing regression analysis (Field, 2024). The cumulative mean values of each variable (CQ, ME, AT, and HOTS) were used in carrying out the diverse tests. Considering that the sample size exceeded 50, normality was evaluated through the assessment of skewness and kurtosis values rather than applying the Kolmogorov-Smirnov or Shapiro-Wilk tests, considered more appropriate for smaller samples (Razali & Wah, 2011). Hair et al. (2010) and Byrne (2013) stated that skewness and kurtosis values between -2 and +2 implied normal data distribution. The results proved that all variables were in the recommended range, thereby ensuring the normality of the data. The presence of multicollinearity was evaluated by assessing tolerance (TOL) and variance inflation factor (VIF) values. Table 4 showed the data set was free of multicollinearity, as depicted by the tolerance and VIF values greater than and less than 0.1 and 10, respectively (Field, 2024; Hair et al., 2010). Moreover, the assumption of homoscedasticity was tested by examining scatterplot residuals (Hong et al., 2023). The results showed that the scatterplot did not exhibit any discernible pattern, such as a funnel or curve, confirming the assumption of homoscedasticity.

Table 4
Normality and Multicollinearity Test

Variables	Skewness	Kurtosis	Collinearity statistics*	
			Tolerance	VIF
CQ	-0.749	0.437	0.186	5.390
ME	-0.728	0.007	0.200	4.997
AT	-0.814	0.619	0.189	5.304
HOTS	-0.606	0.177		

Note: *dependent variable is HOTS; convenience and quality (CQ); motivation and engagement (ME); accuracy and trust (AT); higher order thinking skills (HOTS); variance inflation factor (VIF)

Data Analysis

The association between variables was analyzed using Pearson correlation coefficient (2-tailed) to answer RQ1 to RQ3, and determine the strength. Furthermore, multiple linear regression with the ENTER model was used to provide a detailed diagram of the association between these variables and HOTS of students. The item level was conducted to determine which aspects of each variable the students considered relevant to HOTS development. Previous research also carried out item-level analysis (Lucas et al., 2021). Additionally, multiple linear regression was also used to answer RQ4, with the cumulative mean value of each item on the variable calculated to determine which factors significantly influenced students' HOTS.

The process required testing the unstandardized coefficient (*B*) and standard error (*SE*) to determine the direct effect of each variable, and level of uncertainty, respectively. This also included using the *t* and *p* values to ascertain whether the results were significant. In addition, R^2 was used to determine how much these variables explained the change in students' HOTS. An *F*-statistic test was conducted to ascertain the appropriateness and significance of the regression model.

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Research Results

Students' Perception

Table 5 shows the descriptive statistics extracted from 334 participants in respect to the following four dimensions CQ, ME, AT, and HOTS. CQ dimension had mean scores between 2.982 and 3.216, with CQ3 and CQ4 rated highest (3.216) and lowest (2.982), respectively. For ME, the scores ranged from 3.000 to 3.126, with ME4 and ME1 being the highest (3.126), and lowest (3.000). In AT dimension, AT2 and AT3 scored 3.144 and 3.060, respectively. Finally, HOTS scores were in the range of 3.018 and 3.066, with the highest being HOTS3.

Table 5
Descriptive Statistics (N = 334)

Items	*M*	*SD*	Items	*M*	*SD*
CQ1	3.174	0.813	ME4	3.126	0.829
CQ2	3.084	0.778	AT1	3.090	0.862
CQ3	3.216	0.821	AT2	3.144	0.829
CQ4	2.982	0.952	AT3	3.060	0.868
ME1	3.000	0.890	HOTS1	3.018	0.880
ME2	3.054	0.932	HOTS2	3.054	0.851
ME3	3.042	0.906	HOTS3	3.066	0.850

Table 6
Correlation Results Between Variables

	CQ	ME	AT	HOTS
CQ				
ME	.867**			
AT	.875**	.865**		
HOTS	.890**	.890**	.860**	

Note: $^{**}p < .01$; convenience and quality (CQ); motivation and engagement (ME); accuracy and trust (AT); higher order thinking skills (HOTS)

Correlation and Predictive Association Between CQ and HOTS (RQ1)

Based on Table 6, CQ and HOTS had a significant association ($r = .890$, $p < .01$). Table 7 specifically showed that CQ1 had a significant association with HOTS1 ($B = 0.225$, $p < .001$) and HOTS2 ($B = 0.178$, $p < .001$), and an insignificant correlation with HOTS3 ($B = -0.014$, $p > .05$). CQ2 exhibited a significant impact on all three HOTS indicators, including HOTS1 ($B = 0.230$, $p < .001$), HOTS2 ($B = 0.505$, $p < .001$), and HOTS3 ($B = 0.311$, $p < .001$). Additionally, CQ3 was a significant predictor of the three HOTS indicators, with the results showing that HOTS1 ($B = 0.274$, $p < .001$), HOTS2 ($B = 0.203$, $p < .001$), and HOTS3 ($B = 0.281$, $p < .001$) were significantly influenced. CQ4 had a significant effect on HOTS1 ($B = 0.174$, $p < .01$), HOTS2 ($B = 0.113$, $p < .05$), and HOTS3 ($B = 0.378$, $p < .001$).

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Table 7
Association Between CQ and HOTS Based on Items

Codes	HOTS1		HOTS2		HOTS3	
	B (SE)	*t*	*B (SE)*	*t*	*B (SE)*	*t*
CQ1	0.225 (0.059)	3.813***	0.178 (0.047)	3.779***	-0.014 (0.043)	-0.331NS
CQ2	0.230 (0.062)	3.739***	0.505 (0.049)	10.280***	0.311 (0.045)	6.863***
CQ3	0.274 (0.065)	4.220***	0.203 (0.052)	3.925***	0.281 (0.048)	5.891***
CQ4	0.174 (0.056)	3.129**	0.113 (0.045)	2.540*	0.378 (0.041)	9.222***

Note: $^{NS}p > .05$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Correlation and Predictive Association Between ME and HOTS (RQ2)

In accordance with Table 6, a significant association existed between ME and HOTS ($r = .890$, $p < .01$). Table 8 showed a significant correlation existed between ME1 and all three HOTS indicators, including HOTS1 ($B = 0.324$, $p < .001$), HOTS2 ($B = 0.223$, $p < .001$), and HOTS3 ($B = 0.355$, $p < .001$). Furthermore, a significant correlation existed between ME2 and all three HOTS indicators, namely HOTS1 ($B = 0.242$, $p < .01$), HOTS2 ($B = 0.182$, $p < .01$), and HOTS3 ($B = 0.280$, $p < .001$). ME3 exhibited a significant correlation with HOTS2 ($B = 0.206$, $p < .001$) and HOTS3 ($B = 0.154$, $p < .01$), as well as an insignificant association with HOTS1 ($B = 0.037$, $p > .05$). ME4 showed a significant correlation with HOTS1 ($B = 0.282$, $p < .001$) and HOTS2 ($B = 0.223$, $p < .001$), but not with HOTS3 ($B = 0.080$, $p > .05$).

Table 8
Association Between ME and HOTS Based on Items

Codes	HOTS1		HOTS2		HOTS3	
	B (SE)	*t*	*B (SE)*	*t*	*B (SE)*	*t*
ME1	0.324 (0.051)	6.395***	0.223 (0.052)	4.285***	0.355 (0.046)	7.767***
ME2	0.242 (0.058)	4.156***	0.182 (0.060)	3.042**	0.280 (0.053)	5.327***
ME3	0.037 (0.051)	0.729NS	0.206 (0.052)	3.940***	0.154 (0.046)	3.348**
ME4	0.282 (0.058)	4.825***	0.223 (0.060)	3.731***	0.080 (0.053)	1.522NS

Note: $^{NS}p > .05$; $^{**}p < .01$; $^{***}p < .001$

Correlation and Predictive Association Between AT and HOTS (RQ3)

Table 6 showed a significant association existed between AT and HOTS ($r = .860$, $p < .01$). Furthermore, Table 9 showed that AT1 exerted a significant influence on all HOTS indicators, namely HOTS1 ($B = 0.308$, $p < .001$), HOTS2 ($B = 0.166$, $p < .01$), and HOTS3 ($B = 0.284$, $p < .001$). AT2 had a significant effect on HOTS1 ($B = 0.352$, $p < .001$) and HOTS2 ($B = 0.438$, $p < .001$), as well as an insignificant impact on HOTS3 ($B = 0.033$, $p > .05$). AT3 had a significant effect on all three HOTS indicators, namely HOTS1 ($B = 0.188$, $p < .01$), HOTS2 ($B = 0.259$, $p < .001$), and HOTS3 ($B = 0.559$, $p < .001$).

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Table 9
Association Between AT and HOTS Based on Items

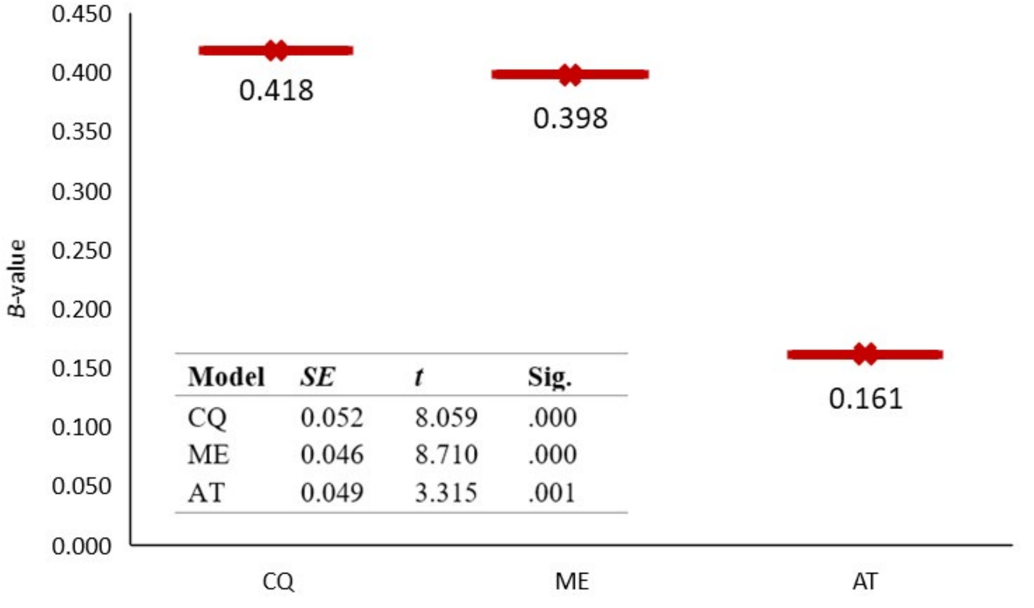
Codes	HOTS1		HOTS2		HOTS3	
	B (SE)	*t*	*B (SE)*	*t*	*B (SE)*	*t*
AT1	0.308 (0.058)	5.317***	0.166 (0.052)	3.168**	0.284 (0.047)	6.110***
AT2	0.352 (0.059)	5.938***	0.438 (0.054)	8.190***	0.033 (0.048)	0.697NS
AT3	0.188 (0.058)	3.268**	0.259 (0.052)	4.980***	0.559 (0.046)	12.084***

Note: $^{NS}p > .05$; $^{**}p < .01$; $^{***}p < .001$

Factors that Mainly Influenced the Development of HOTS (RQ4)

Figure 1 shows an analysis of the variables, namely CQ, ME, and AT that play an essential role in developing HOTS using ChatGPT. The results obtained were based on the cumulative mean value of each item on the variable scale, used to calculate *B*, *SE*, *t*, and significance values (*p*-value). Additionally, the research showed that the variable CQ exerted the most significant influence on HOTS, with a *B* value of 0.418 ($p < .001$). ME variable showed a significant impact, with *B* value of 0.398 ($p < .001$). AT exerted a comparatively weaker influence, with *B* value of 0.161 ($p < .01$). The overall model exhibited robust explanatory power, with R^2 and *F*-value of 0.854 and 642.071 ($p < .001$), respectively.

Figure 1
Factors that Mainly Influence the Development of HOTS



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Discussion

CQ and Higher-Order Thinking Skills

The results outlined the significant and predictive association between CQ of ChatGPT and students' HOTS in physics inquiry. In accordance with Table 6, a strong correlation (r = .890, p < .01) existed between CQ and HOTS, suggesting that students who rated ChatGPT highly in terms of CQ probably developed critical thinking and problem-solving abilities.

Specific CQ dimensions had varying degrees of impact on different aspects of HOTS, as shown in Table 7. CQ1 (ease of understanding) was positively associated with critical thinking (HOTS1) and in-depth analysis (HOTS2), but had an insignificant influence on complex problem-solving (HOTS3). However, the clarity of ChatGPT in presenting information fostered analytical thinking, resulting in the capacity to facilitate advanced problem-solving skills. This is in line with previous research (Dao & Le, 2023; Tabib & Alrabeei, 2024), which focused on the challenges faced by AI tools in supporting the integration of multiple complex ideas—an essential component of resolving intricate problems (Herrmann et al., 2023; Uesaka et al., 2022).

CQ2 (concept linkage), CQ3 (response speed), and CQ4 (quality of explanation) had significant effects on all HOTS dimensions. The ability of ChatGPT to connect various physics concepts (CQ2) had been proven to be a critical factor in enhancing students' problem-solving and IBL skills, as the integration of different theoretical perspectives aided in the understanding of complex phenomena (Asrizal et al., 2023; Kieser et al., 2023; Liang et al., 2023; Usmeldi, 2015). This result was consistent with Almogren et al. (2024), who outlined the role of technologies that promoted conceptual integration in fostering deep learning and practical application of theoretical knowledge.

The speed of ChatGPT responses (CQ3) significantly contributed to the learning process, particularly engaging students with inquiry-based tasks. Previous research reported that immediate feedback facilitated reflection, thereby enhancing learning (Al Shloul et al., 2024; Desnita et al., 2022; Festiyed et al., 2022). This was in line with Ngo (2023), which stated the importance of timely responses in facilitating quick conceptual exploration and deeper cognitive engagement. Similarly, the quality of explanations (CQ4) supported critical thinking, offering detailed context-rich information that motivated students to engage in thorough analysis of the topics (Gerhátová et al., 2021; Siverling et al., 2021).

ME and Higher-Order Thinking Skills

The results proved a significant correlation existed between ME and HOTS during physics inquiry (r = .890, p < 0.01), as shown in Table 6. Students who were more motivated and engaged while using ChatGPT exhibited more robust critical thinking and problem-solving skills.

Based on specific ME dimensions, Table 8 showed that ME1 (increased motivation after using ChatGPT) and ME2 (enjoyment in learning) strongly correlated with all HOTS indicators. The results outlined the crucial role of ME in promoting student ability to think critically and conduct in-depth analysis (Indriani et al., 2024; Tica & Krsmanović, 2024). The individuals who were highly motivated after using ChatGPT also exhibited better critical thinking and problem-solving abilities. This supported previous research that intrinsic motivation was a critical driver of inquiry-based learning environments (Almazrou et al., 2024; Krupp et al., 2024; Lee et al., 2024; Wang et al., 2024). The finding was consistent with the research by Al-Mughairi and Bhaskar (2024), who stated educational technologies improved student motivation, enhancing engagement with complex tasks.

ME3 (increased motivation to learn) significantly correlated with in-depth analysis (HOTS2) and complex problem-solving (HOTS3) but had an insignificant effect on critical thinking (HOTS1). This implied that while motivation prompted deeper analysis and resolution of complex problems, the quality of information provided by ChatGPT (as evidenced in CQ dimension) played a crucial role in fostering initial critical thinking. The nuance was supported by Meulenbroeks et al. (2024), that motivation and other related factors required critical thinking without high-quality, thought-provoking instructional content.

In line with this perspective, ME4 (satisfaction with ChatGPT) significantly influenced critical thinking (HOTS1) and in-depth analysis (HOTS2) but had an insignificant impact on complex problem-solving (HOTS3). Moreover, satisfaction with the tool promoted critical thinking and analysis, motivating students to solve more intricate problems. This could depict additional support, such as teacher guidance or collaborative learning strategies, to address complex challenges (Alshahrani, 2023; Kim et al., 2024). Similarly, Hmoud et al. (2024) stated that technology-based tools could not completely replace human interaction in developing higher-order cognitive skills required for complex problem-solving.

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AT and Higher-Order Thinking Skills

The results proved a significant correlation existed between AT and HOTS during physics inquiry (r = .860, p < .01), as shown in Table 6. This implied that accessibility to accurate and reliable information played an essential role in fostering student critical thinking and problem-solving abilities.

Based on Table 9, AT1 (accuracy of information) and AT3 (trust in information accuracy) significantly influenced all three HOTS indicators. Students who trusted the accuracy and reliability of information provided by ChatGPT exhibited more robust performance in HOTS1, HOTS2, and HOTS3. It outlined the importance of accurate information in supporting students' ability to make evidence-based decisions, a major component in physics inquiry (Huschens et al., 2023). These results were consistent with the research by Johnson et al. (2023), that students probably engaged in higher-order cognitive tasks such as critical thinking and problem-solving, if the provided information is accurate.

AT2 (up-to-date information) significantly correlated with HOTS1 and HOTS2 but had an insignificant impact on complex problem-solving (HOTS3). Timely information is crucial for fostering essential critical thinking and analysis. However, there is a need to motivate students to solve more complex, multifaceted problems. Resolving these problems may require profound and nuanced information, including a comprehensive understanding of basic principles and concepts rather than recent updates (O'Mahony, 2003). Meanwhile, complex problem-solving in physics demands an integration of up-to-date and foundational knowledge, explaining why AT2 had an insignificant impact on HOTS3.

Factors that Mainly Influence Higher-Order Thinking Skills

The analysis conducted on factors influencing HOTS in physics inquiry learning using ChatGPT showed that CQ played the most significant role. CQ was identified as the strongest predictor, surpassing both ME and AT, with a B value of 0.418 (p < .001). The ease of use and quality of information provided by ChatGPT are crucial in helping students enhance critical thinking, in-depth analysis, and complex problem-solving abilities. These results are in line with prior research, outlining the importance of user-friendly and high-quality digital tools in educational settings (Almazrou et al., 2024; Kieser et al., 2023). In addition, when tools such as ChatGPT are integrated into well-structured inquiry-based learning environments, it enables students to connect theories, and understand abstract concepts, including engaging in higher-order cognitive tasks (Avsheniuk et al., 2024).

ME was found to significantly impact HOTS, with B value of 0.398 (p < .001). The result outlined the critical role that students' motivation, particularly the intrinsic drive to learn and engage with ChatGPT, fostered cognitive skills such as problem-solving and critical thinking. This is consistent with previous research that focused on the role of motivation in educational technology (Bettayeb et al., 2024; Krupp et al., 2024). Students explore learning materials more profoundly and tend to actively participate in analysis and inquiry, when motivated.

The variable AT had a comparatively weaker influence on HOTS, with B value of 0.161 (p < .01). Meanwhile, accuracy and trust in the information provided by ChatGPT fostered critical thinking and evidence-based decision-making. These factors were perceived as secondary compared to CQ of the tool. It supported the idea that students value accurate and trustworthy information, leading to easy access and interaction with the tool, thereby having a direct impact on the learning outcomes (Guo & Lee, 2023).

The high R-squared value (R^2 = 0.854) further supported the robustness of the model, depicting that the combined effects of CQ, ME, and AT explained 85.4% of the variance in HOTS. The robust model fit suggested that ChatGPT supported students' cognitive development in IBL environments. Furthermore, the effectiveness of ChatGPT in facilitating critical thinking and problem-solving reflects the broader potential of AI tools in education, specifically when integrated with pedagogical methods, namely IBL (Chinonso et al., 2023).

Several research also reported high R^2 values, supporting the effectiveness of AI tools such as ChatGPT in educational contexts. For example, Salifu et al. (2024) reported R^2 of 0.801 for economics students' behavioral use of ChatGPT. Sapriati et al. (2024) obtained R^2 of 0.849 in measuring inquiry learning skills, while Amer jid Almahri et al. (2024) realized an even higher R^2 of 0.917 for undergraduate behavioral intention toward chatbots. These high values across different educational contexts validated the potential of AI tools to influence students' learning outcomes significantly.

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Limitations and Future Research

Several limitations should be acknowledged, despite the valuable insights gained from the research. First, the sample size represented a broader population of students using ChatGPT for physics IBL. The reliance on self-reported data introduced biases (Giromini et al., 2022), as students tend to overestimate personal abilities or the effectiveness of ChatGPT due to social desirability. Additionally, the research focused mainly on students' perceptions, which partially captured the actual learning outcomes and skills developed through the use of ChatGPT. Second, the cross-sectional design limited the ability to draw causal inferences regarding the impact of this tool on critical thinking and problem-solving skills. Longitudinal analyses would be beneficial in assessing the long-term effects of integrating ChatGPT into physics IBL, including determining how students' perceptions and skills evolved. Third, the research did not explore the specific contexts in which ChatGPT was used, such as the topics or inquiry activities. Variations in content and context influenced students' experiences and perceptions of the tool. Future research should consider these contextual factors to obtain a better understanding of how ChatGPT can be effectively integrated into different learning scenarios.

Several avenues for future research were suggested. First, these should include a more diverse and extensive sample of students from diverse educational institutions and geographic regions. This enhanced the generalizability of the results and allowed for comparisons across varied contexts. Second, longitudinal research provided deeper insights into how the integration of ChatGPT in IBL affected critical thinking and problem-solving skills over time. It was intended to help educators understand the sustained impact of technology on learning outcomes and inform pedagogical practices.

Exploring the effectiveness of ChatGPT in different physics topics and inquiry activities would be beneficial. Future research should investigate how specific questions or inquiry tasks influenced students' engagement with the tool and subsequent learning outcomes. Additionally, examining how certain factors, namely teaching style (Villar-Aldonza, 2023), classroom dynamics (Vashishth et al., 2024), and peer collaboration (Burns et al., 2024; Li & Goos, 2023) interact with the use of ChatGPT provides valuable insights into optimizing the integration in educational settings.

Conclusions and Implications

In conclusion, this research examined the use of ChatGPT (CQ, ME, and AT) by upper-secondary students to develop HOTS as predictors of physics inquiry. The results showed several major aspects first, CQ dimensions strongly correlated with HOTS. In this dimension, concept linkage, response speed, and explanation quality were significant predictors of HOTS. Second, MA dimension significantly correlated with HOTS. Additionally, increased motivation to learn after using ChatGPT and enjoying the process were identified as significant predictors of HOTS. Third, the AT dimension significantly correlated with HOTS because the accuracy of the information and student trust were essential predictors. Finally, the factors influencing the development of HOTS in the context of physics inquiry learning using ChatGPT proved that CQ played the most significant role. Therefore, this research provided insights for optimizing AI technology in science education, outlining the potential contribution of ChatGPT in supporting IBL.

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Declaration of Interest

The authors declare no competing interest.

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